

# FUZZY NONLINEAR REGRESSION MODEL FOR RAILWAYS RIDE QUALITY

Jairo Maya Toro  
Resercher Teacher  
EAFIT University  
Medellín – Colombia  
jmaya@eafit.edu.co

Sophie Hennequin  
Asistant Profesor  
National Engineering School of Metz (ENIM)  
Metz-Francia  
hennequin@enim.fr

Dorian W Raigosa M.  
Master Student  
EAFIT University  
Medellín – Colombia  
draigosa@ eafit.edu.co

Leonel Castañeda Heredia  
Researcher Teacher  
EAFIT University  
Medellín-Colombia  
lcasta@eafit.edu.co

## ABSTRACT

The portable diagnosis system - SPD - evaluates the safety and ride quality aspects of the railway vehicles and the technical condition of the rail-vehicle interface. The objective of this article is to estimate the nonlinear regression model associated to the ride quality or motion behaviour, by applying fuzzy clustering algorithms on the geometric data obtained from the technical condition of the railway-vehicle interface and the measuring of the quasi-static lateral acceleration  $y_{qst}^*$  in different vehicles.

The performance will be evaluated by comparing the measured acceleration  $y_{qst}^*$  with the acceleration calculated with our model  $y_{qstM}^*$  for 15 different vehicles. The obtained results will be then compared with the results of the multiple linear regression model used previously for the same purpose [16].

Index terms: Fuzzy clustering, railways ride quality, fuzzy nonlinear regression.

## 1. INTRODUCTION

The ride quality on the passenger railways vehicles, according to the UIC518<sup>1</sup> from the International Union of Railways, has relation with the value for acceleration  $y_{qst}^*$ , this normative says that for ride quality it should has a value limit of  $1,5 m/s^2$  [7]. Due to the high cost involved in the measuring of the acceleration  $y_{qst}^*$  to each vehicle, it is necessary to obtain a tool (model) that allows to predict the behaviour of the acceleration  $y_{qst}^*$  according to the measured the 23 geometric variables, which are routinely measured in the normal preventive maintenance routine of the railway, without the need of making a  $y_{qst}^*$  measuring process. Many of the traditional method used to solve this problem are based on global models like Polynomials (ARMA, ARX,NARMX,NARMAX) [4],[6],[12], radial basis functions and neural network [1],[2],[3],[5], fuzzy clustering [6],[13], among others some of then used

---

<sup>1</sup> Testing and approval of railway vehicles from the point of view of their dynamic behaviour-Safety-Track fatigue – Ride quality.

in similar railways application in the world [20],[21].

The fuzzy clustering is to approximate a nonlinear regression problem by decomposing into several local linear models; this approach has advantages in comparison with global nonlinear models [13]. The model structure is easy to understand and interpret, both qualitatively and quantitatively. Besides, the approach has computational advantages and lends itself to straightforward adaptive and learning algorithms. To show the feasibility of approach, we will compare the obtained results using fuzzy clustering with the Babuska toolbox [13], with the results obtained with the multiple linear regression model used previously for the same purpose [16].

This article is part of the development of SPD (Portable Diagnostic System)[16],[22],[23],[24] [17],[18],[19], which consist of the measurement of the vehicle's variables allowing the identification of the technical condition for the vehicle-railway interface.

The paper is organized as follows. In section 2, we will introduce the element for the regression used in the SPD system. In section 3 we will review the nonlinear regression; section 4 will detail the fuzzy clustering methodology and sections 5 and 6 will show the results, comparison with NRL (Multiple nonlinear regression)[16] and conclusions respectively.

## 2. STUDIED SYSTEM

The Metro system of Medellín was created the 31<sup>st</sup> of May, 1979 by the Medellín municipality and the Antioquia Department, allowing the creation of the Metro de Medellín Company.

**Figure 1. Metro System of Medellín**



Metro system of Medellín photographic file

Description of the railroad:

- **Line A:** Paralell to the Medellín River and with a length of 23,2 km, it's provided with 19 stations in direction North to South.
- **Line B:** It starts from the centre of the city in the San Antonio B Station and goes west direction. It has a length near to 5,6 km and it counts with 7 stations.
- **Linking Line:** it connects the two lines described above and has a length of 3,2 km.
- **Line K:** It is a cable transport system that connects the Acevedo Station. It consists of 4 stations and has a length of 2,4 km.

In order to extract the data, both the estimators given by the standard UIC 518 and the geometric variables, the complete railroad of the train is taken and the measuring points were classified by sections, just as the standard UIC 518 recommends. The three zones proposed by the standard are considered: tangent tracks, large radius curve tracks and short radius curve tracks; however, the length of the sections that compose the different zones was adapted according to the distribution of the Line A road of the Metro system. The considered lengths were:

- Tangent track: 160 m
- Large radius curve track: 70 m
- Short radius curve track: 70 m

### 2.1. Data acquisition

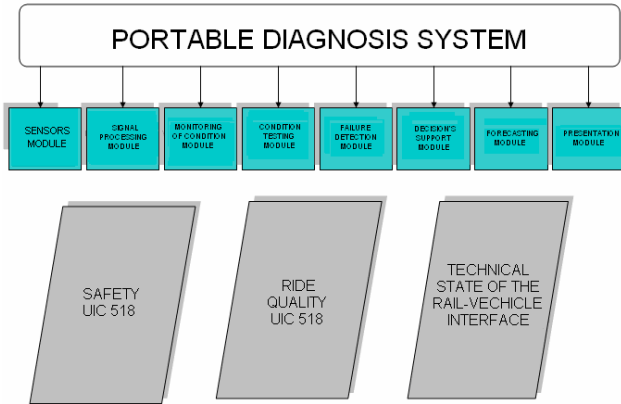
The Portable Diagnostic System - SPD is a unique development for the railway systems, which apart from evaluating safety, ride quality and monitoring the condition of the geometric parameters of the track - vehicle interface, also allows to carry out the multidimensional monitoring of the condition and to determine the generalised failures of passenger vehicles of the Metro de Medellín [16], [22],[23],[24].

To develop this diagnosis tool, different methodologies were used, grouping several modern and effective methods in the diagnosis tasks, which go from the selection of measurement points, through the method of evaluation of the UIC 518 standard until the utilization of an optimised forecast method [7],[16], [22],[23],[24].

The system is composed by eight modules: sensors, signal processing, monitoring of the condition, condition testing, incipient failures detection in the wheel-rail interface, decisions support, forecast and

presentation. In figure 2, the SPD module structure appears

**Figure 2. Module of the SPD**



The obtained signal by the SPD allows calculating the lateral and longitudinal forces that are generated in the vehicle along the track which are necessary for the safety evaluation.

The UIC 518 standard describes the experimental procedures to follow in order to carry out the motion tests and the analysis of the results, in terms of quality and rolling from the point of view of the dynamic behaviour in relation to the safety, railroad wear and motion behaviour (ride quality) with the purpose of an approval for the international railway traffic.

Table 1 presents the different estimators considered by the standard. It was necessary to acquire acceleration and forces signals in different parts of the train to calculate the estimators [5].

**Table 1. Estimators for safety, ride quality and fatigue track according to the UIC 518 Standard.**

Estimator	Description	Units	Limit Value
SY2m	Sum of guiding forces for axle	kN	66.7
SY2m (99,85%)	Sum of guiding forces for axle, Percentile 99.85%	kN	66.7
SY2m (0,15%)	Sum of guiding forces for axle, Percentile 0.15%	kN	66.7
sSY	Weighted r.m.s of Sum of guiding forces por axle.	kN	33.3
Yqst	Quasi-static force between wheel and rail	m/s <sup>2</sup>	60
y:*q	Lateral acceleration in the vehicle body	m/s <sup>2</sup>	2.5
y:*q (99,85%)	Lateral acceleration in the vehicle body, Percentile 99.85% .	m/s <sup>2</sup>	2.5

Estimator	Description	Units	Limit Value
y:*q (0,15%)	Lateral acceleration in the vehicle body, Percentile 0.15%.	m/s <sup>2</sup>	2.5
sy:*q	Weighted r.m.s of Lateral acceleration in the vehicle body.	m/s <sup>2</sup>	0.5
y:*qst	Quasi-static acceleration in the vehicle body.	m/s <sup>2</sup>	1.5
z:*q	Vertical acceleration in the vehicle body.	m/s <sup>2</sup>	2.5
z:*q (99,85%)	Vertical acceleration in the vehicle body, Percentile 99.85%.	m/s <sup>2</sup>	2.5
z:*q (0,15%)	Vertical acceleration in the vehicle body, Percentile 0.15%.	m/s <sup>2</sup>	2.5
sz:*q	Weighted r.m.s of Vertical acceleration in the vehicle body.	m/s <sup>2</sup>	0.75
I	Cant deficiency	mm	150

Because this article is limited to the ride quality evaluation, the estimator to use will be the acceleration  $y_{qst}$ . According to the UIC 518 standard [7], the limit value of this acceleration of  $1,5 m/s^2$ , defines the ride quality or motion behaviour of the vehicle.

This estimator is obtained from the lateral acceleration signal, taken form the passenger’s box (vehicle). These measurements are filtered by a digital filter, topology Butterworth, order 8 and cutting frequency of 20 Hz.

## 2.2. Geometric variables

Among the current maintenance routines of the railway system, different geometric variables that give an idea of the technical condition of the rail, are measured. These are presented in Table 2.

**Table 2. State condition variables**

Geometric Variable	Description	Units	Limit Value
X1	Equivalent conicity with standard deviation of 1.25 under the UK method.	N/A	
X2	Equivalent conicity with standard deviation of 2.5 under the UK method.	N/A	
X3	Equivalent conicity with standard deviation of 3.75 under the UK method.	N/A	
X4	Maximum speed vehicle	km/h	80
X5	Standard deviation of the vertical alignment.	mm	2.3

X6	Standard deviation of the horizontal alignment.	mm	1.5
X7	Cant deficiency	mm	150
X8	Curve radius	m	0
X9	Horizontal alignments	mm	3
X10	Diferencia de altura entre la cabeza del hilo alto y bajo.	mm	3
X11	Vertical alignments	mm	10
X12	Gap between the internal rail faces.	mm	3
X13	Synthetic coefficient of the railroad quality.	mm	0
X14	Vertical wear of the head rail for the high rail (east-south)	mm	12
X15	Vertical wear of the head rail for the high rail (west-north)	mm	12
X16	r.m.s of the corrugation for the high rail for a wave length between 30 and 100 mm.	mm	10
X17	Excess percentage for the high rail for a wave length between 30 and 100 mm.	%	50
X18	r.m.s of the corrugation for the high rail for a wave length between 100 and 300 mm.	mm	20
X19	Excess percentage for the high rail for a wave length between 100 and 300 mm.	%	50
X20	r.m.s of the corrugation for the low rail for a wave length between 30 and 100 mm.	mm	10
X21	Excess percentage for the low rail for a wave length between 30 and 100 mm.	%	50
X23	r.m.s of the corrugation for the low rail for a wave length between 100 and 300 mm.	mm	20
X24	Excess percentage for the low rail for a wave length between 100 and 300 mm.	%	50

### 3. PRINCIPLES OF NONLINEAR REGRESSION.

Generally, fuzzy systems are approximations of functions. Because of this, they can also be used in nonlinear regression problems. The nonlinear regression is a modelling of the static dependence of the answer of a variable called regressor, where:

$y \in Y \subset \mathfrak{R}$ , is a regression vector,  $x = [x_1, x_2, \dots, x_p]^T$ , over the  $X \subset \mathfrak{R}^p$  domain. The elements of the regression vector can be called regressors and the X domain can be called regressor space. The system generated by the data can be described by:

$$y \approx f(x) \quad (3.1)$$

The deterministic function  $f(\cdot)$  captures the dependence of  $y$  in  $x$ , and the symbol  $\approx$  reflects the characteristics of  $y$  that are not exact in function of  $x$ . The objective of the regression is to use the data in order to build a function  $F(x)$  as an approximation to  $f(x)$  not only because of the data, but because of the domain itself. The definition of a reasonable approximation depends on the purpose for which the model is build. If the objective of the model is to obtain predictions of  $y$ , accuracy must be the most relevant criteria. The accuracy insufficiency is usually known as the integral error over the domain.

$$I = \int_x \|f(x) - F(x)\| dx \quad (3.2)$$

Generally, this error can not be computed, since the value of  $f$  is only known with the availability of the data. However, the average of the error prediction of the available data is often used

$$J = \frac{1}{N} \sum_{i=1}^N \|f(x_i) - F(x_i)\| \quad (3.3)$$

Where N is the number of data in the sample.

Apart from the prediction accuracy, the objective can also be to obtain a model that can be used in order to analyse and understand the real properties of the data generator system. The potential of the fuzzy models is that they describe the systems as a collection of simple local sub-models expressed by rules. The rules can be formulated using natural language, which is more understandable than a mathematical language. The rules can also be combinations of analytical models commonly used in the control field of engineering, like the local linear models in Takagi-Sugeno [12].

#### 3.1. NONLINEAR REGRESSION MODEL

The input of our model are the 23 geometric variables of the rail state and with them, the modelled acceleration  $Y_{gstM}$  is calculated.

An arrangement is conformed having a line for each one of the  $n$  geometric variables measured for each section, and a column for each one of the  $N$  sections. This arrangement is called matrix of observation  $X$  (regresor space).

$$Z = \begin{bmatrix} z_{11} & z_{12} & \cdots & z_{1N} \\ z_{21} & z_{22} & \cdots & z_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{nN} \end{bmatrix}$$

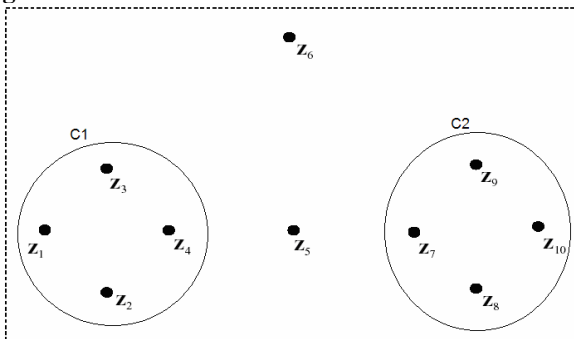
Traditionally, the clustering terminology defines the columns of the matrix of observation  $X$  as characteristics or attributes, while the lines are called patterns or objects.

#### 4. FUZZY CLUSTERING LOGIC

It is defined as *cluster*, the sub-set of data that are more similar between them than with other data from another sub-set.

There are different types of data association or clustering, one of the most popular is the “*Hard clustering*” which refers to grouping the data in specific clusters mutually exclusive (see Figure 3), meaning that a data belongs only to one cluster and not to several clusters at the same time. In figure 3 the data  $z_5$  could belong to both clusters  $c_1$  and  $c_2$ , this data is not had into account when using the Hard cluster.

Figure 3. Data set



(Delf center for System, TU Delft, BABUSKA. R)

It is reasonable to think that in the frontier of two clusters  $c_1$  and  $c_2$  there are some points that have a degree of belonging in both cluster. The algorithm *c-means* (Bezdek in Jang, 1997) allows that each point belongs to a cluster with certain degree of belonging, so each point belongs to several clusters. This makes

the fuzzy clustering, in some real situations, to be more natural than the Hard clustering.

#### 4.1. Partition Fuzzy

The objective of the clustering is to divide the data set  $Z = \{z_1, z_2, \dots, z_N\}$  in  $c$  clusters ( $2 \leq c \leq N$ ), that partition  $U = [u_{ik}]$ , where  $u_{ik}$  is the degree of belonging of the  $i$  point to the cluster  $k$ .  $U$  represents a fuzzy partition if the points fulfil the following conditions:

$$u_{ik} \in [0,1] \quad 1 \leq i \leq c, \quad 1 \leq k \leq N, \quad (4.1.1)$$

$$\sum_{i=1}^c u_{ik} = 1 \quad 1 \leq k \leq N \quad (4.1.2)$$

$$0 < \sum_{k=1}^N u_{ik} < N \quad 1 \leq i \leq c, \quad (4.1.3)$$

Definig the fuzzy partition space as:

$$M_{fc} = \left\{ U \in \mathfrak{R}^{c \times N} \mid u_{ik} \in [0,1], \forall i, k; \sum_{i=1}^c u_{ik} = 1, \forall k; 0 < \sum_{k=1}^N u_{ik} < N, \forall i \right\}$$

#### 4.2. Algorithm Fuzzy C-Means

There are different algorithms for fuzzy clustering, the most used is the “*C-Mean*” algorithm. This algorithm makes the data partition minimizing the objective function [6]:

$$J(Z; U, V) = \sum_{i=1}^c \sum_{k=1}^N u_{ik}^m d_{ik}^2 \quad (4.2.1)$$

Where:

$$Z = \{z_1, z_2, \dots, z_N\} \quad (4.2.2)$$

Is the data set to classify.

$$U = [u_{ik}] \in M_{fc} \quad (4.2.3)$$

Is the partition matrix  $Z$ .

$$V = [v_1, v_2, \dots, v_c], \quad v_i \in \mathfrak{R}^n \quad (4.2.4)$$

Is the centre vector (clusters) to find.

$$d_{ik}^2 = \|z_k - v_i\|^2 \quad (4.2.5)$$

Is the Euclidian norm, distance from the data to the center of a cluster.

$$m \in [1, \infty)$$

Is an exponent that determines the fuzziness of the obtained clusters.

The steps of the algorithm are:

- To select a belonging matrix
- To start the number of clusters
- To calculate the centroid of the clusters,

$$v_i = \frac{\sum_{k=1}^N u_{i,k}^m z_k}{\sum_{k=1}^N u_{i,k}^m} \quad (4.2.6)$$

- To calculate the Euclidean distance
- $$d_{ik} = (z_k - v_i)^T (z_k - v_i) \quad (4.2.7)$$

- To update the belonging matrix
- $$u_{ik} = \frac{1}{\sum_{j=1}^c \left( \frac{d_{ik}}{d_{jk}} \right)^{\frac{1}{m-1}}} \quad (4.2.8)$$

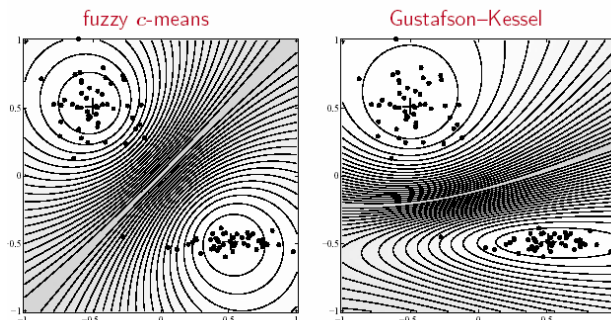
The equation (4.2.6) gives a value  $v_i$  that is the weighted average of the data belonging to a cluster, where the weights are the belonging functions.

This algorithm presents the following disadvantages:

- The final results depend on the final partition.
- The number of cluster is defined at the beginning of the algorithm
- The Euclidean distance method allows detecting only spherical clusters.

This very last disadvantage is a drawback, because the most ideal shape of data grouping is given by an ellipse, so the most appropriated algorithm is the one called ‘‘Gustafson-kessel’’, because this one looks for hyper ellipsoids clusters, which detect very well the quasi-linear behaviour of the data.

**Figure 4. Clusters of different shape**



### 4.3. Gustafson-kessel (GK) Algorithm

This algorithm is found among the adaptive distance algorithms. This one extends the fuzzy c-means by choosing a different norm  $B_i$  for each cluster instead of keeping it constant.

$$d_{ik}^2 = (z_k - v_i)^T B_i (z_k - v_i) \quad (4.3.1)$$

Where  $B_i$  are the possible optimisation matrixes of the objective function, and correspond to the covariance of each cluster.

Then, the objective function is defined as follows:

$$J(Z; U, V) = \sum_{i=1}^c \sum_{k=1}^k u_{ik} d_{ikB_i}^2 \quad (4.3.2)$$

In order to obtain a viable solution,  $B_i$  must be limited somehow. In this case, we will keep its volume constant by fixing the determinant of  $B_i$ .

$$B_i = [\rho_i \det(F_i)]^{\frac{1}{2}} F_i^{-1} \quad (4.3.3)$$

Where  $F_i$  is the covariance matrix for each cluster.

The GK algorithm fits with the purpose of identification because it has the following characteristics:

- The cluster dimension comes limited by the measure of the distance and by the definition of the clusters prototype as a point.
- In comparison with other algorithms, GK is relatively insensitive to the initialization of the partition matrix.

Once we have the groups of data, the next step is to derivate the interference rules which identify a fuzzy model. To achieve that, there are different types like:

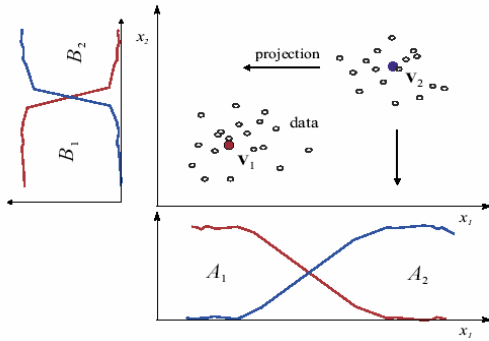
**Mandami:** Fuzzy rules with fuzzy antecedents and fuzzy consequents.

**Takagi-Sugeno (TS):** Fuzzy rules with fuzzy antecedents and consequents that could be expressed in a simple way like a first order linear model[12].

Because the TS fuzzy model is an effective tool for the approximation of nonlinear systems based in the information of inputs and outputs through interpolation of the local linear models, which for this case are determined by the cluster, we use this TS model in the solution of the identification of the model we are looking for.

The solution consists of projecting the belonging of the obtained cluster in the desired space (Figure 5), thus obtaining belonging functions from the cluster.

**Figure 5. Extraction of rules by fuzzy clustering**



(Delft centre for System, TU Delft, BABUSKA R)

#### 4.4. Takagi-Sugeno Model

In the Takagi-Sugeno model, the consequent rules are function of the inputs:

$$R_i : \text{If } x \text{ is } A_i \text{ Then } y_i = f_i(x), i = 1, 2, \dots, K \quad (4.4.1)$$

Where  $x \in \mathfrak{R}$  is the input variable (antecedent),  $A_i$  is a multidimensional fuzzy set (cluster),  $y_i$  is the output variable (consequent),  $R_i$  is the  $i$ th rule and  $K$  is the number of rules of the rules set.

The consequent function can be linearly expressed as:

$$y_i = a^T_i x + b_i \quad (4.4.2)$$

(4.4.2) in (4.4.1):

$$R_i : \text{If } x \text{ is } A_i \text{ Then } y_i = a^T_i x + b_i \quad (4.4.3)$$

Given the outputs of the individual consequents  $y_i$ , the global output and the Takagi-Sugeno model

(defuzzification) is calculated by:

$$y = \frac{\sum_{i=1}^K \beta_i(x) y_i}{\sum_{i=1}^K \beta_i(x)} \quad (4.4.4)$$

Where  $\beta_i$  is the commitment degree of the antecedent of the  $i$ th rule, calculated as the belonging degree of  $x$  in the interior of the  $A_i$  cluster:

$$\beta_i(x) = \mu_i(x) \quad (4.4.5)$$

Normalising,

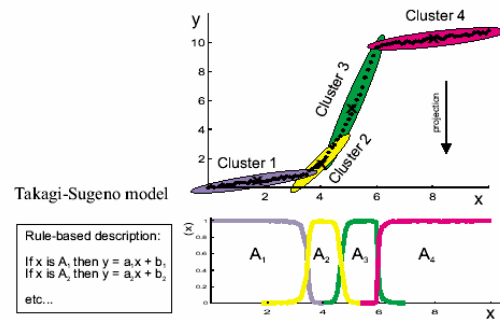
$$h_i(x) = \frac{w_i(x)}{\sum_j w_j(x)} \quad (4.4.6)$$

So the TS model could be interpreted as a quasi-linear model with dependence on the input  $x$  parameter.

$$y = \sum_{i=1}^r h_i(x) \cdot (a_i^T \cdot x + b_i) \quad (4.4.7)$$

Figures 6 and 7 show an example of a function  $y = f(x)$ , represented by four TS rules. The antecedent of each rule defines a valid zone (fuzzy) for the correspondent linear model of the consequent. The global output function  $y$  is calculated through the weighting of the local linear models.

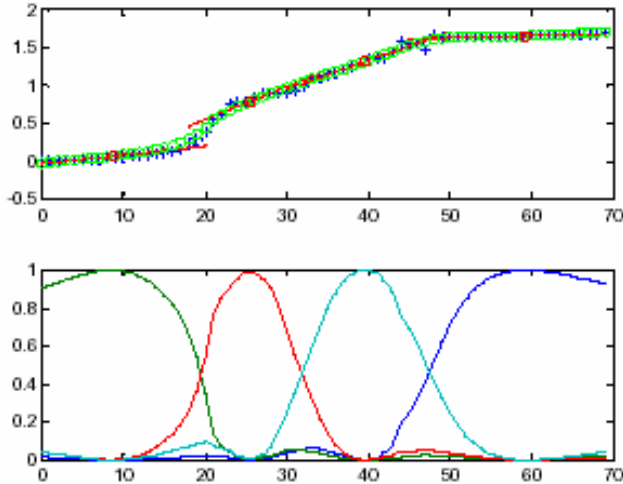
**Figure 6. Takagi-Sugeno fuzzy clustering**



(Delft centre for System, TU Delft, BABUSKA R)



**Figure 7. GK y TS fuzzy clustering**



## 5. NUMERICAL RESULT

During this work, the toolbox developed by the professor Robert Babuska [13] from the Delft Centre for System and Control was used. This tool was developed to be worked on MATLAB.

Once the information is collected from the matrix of observations  $X$ , is taken to a pre-processing that consists in centering the matrix.

**Figure 8. Normalization of a matrix**

$$Z = \begin{bmatrix} z_{11} & \dots & z_{1j} & \dots & z_{1K} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ z_{i1} = \frac{x_{i1} - \bar{x}_1}{s_1} & \dots & z_{ij} = \frac{x_{ij} - \bar{x}_j}{s_j} & \dots & z_{iK} = \frac{x_{iK} - \bar{x}_K}{s_K} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ z_{n1} & \dots & z_{nj} & \dots & z_{nK} \end{bmatrix}$$

término general

Where  $\bar{x}$  is the measure of each variable  
 $S$  is the standard deviation.

The quality of the model is evaluated by calculating the average error (equation (2.3)), its equivalent in the used toolbox, corresponds to the percentile variance accounted (VAF)[13], between the real and the estimated data.

This coefficient is obtained between two signals:

$$VAF = 100\% \cdot \left[ 1 - \frac{\text{var}(y1 - y2)}{\text{var}(y1)} \right] \quad (5.1)$$

Where the value of VAF will be 100% if both signals are equal. If the values are quite different, the value of VAF will tend to zero.

For each vehicle, the following procedure was followed:

- The matrix is normalised.
- The matrix is divided into two sections, one for the identification of the model and the other to carry out the verification of the obtained model.
- The real acceleration with the obtained model by multiple linear regression was plotted [14],[15]. This was also used to determine the ride quality model [16], because of that it will be a reference to validate our results and the obtained result by the fuzzy clustering method.
- The VAF coefficient is calculated to determine the accuracy of the model compared with the real data.

The best results were obtained using the toolbox with the following parameters:

- FM.c = 12;                   % number of clusters
- FM.m = 2.8;               % fuzziness parameter
- FM.tol = 0.1;             % termination criterion
- FM.ante = 2;           % 2 - projected MFS
- FM.cons = 2;           % 2 - weighted LS

Where FM is the defined structure by Babuska in MATLAB for the parameters of the toolbox.

In table 3, we present the obtained results with the fuzzy nonlinear regression model and the obtained results with the multiple regression model [16].

**Table 3. Results**

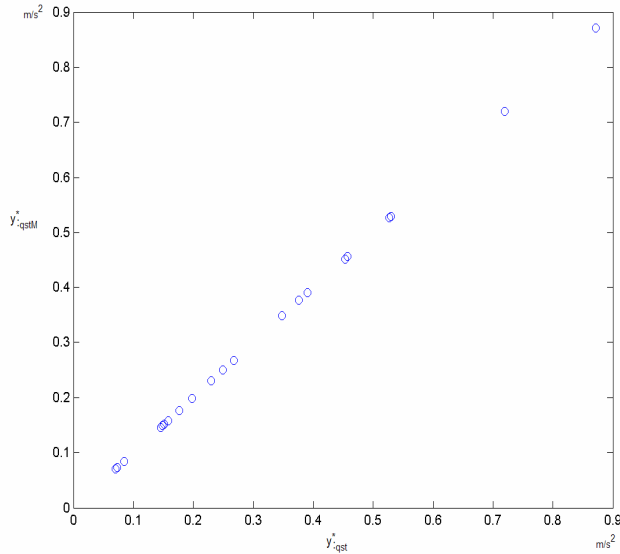
Item	Unidad	Regresión Lineal(%VAF)	Fuzzy Clustering(%VAF)
1	05	76.16	100
2	09	97.52	100
3	10	80.01	95.53
4	12	86.89	100
5	13	87.03	99.17
6	15	78.69	100
7	17	87.19	100
8	19	92.66	100
9	22	86.81	100
10	24	94.7	100
11	34	84.93	100
12	35	70.86	99.07
13	38	77.83	100
14	40	94.15	92.28



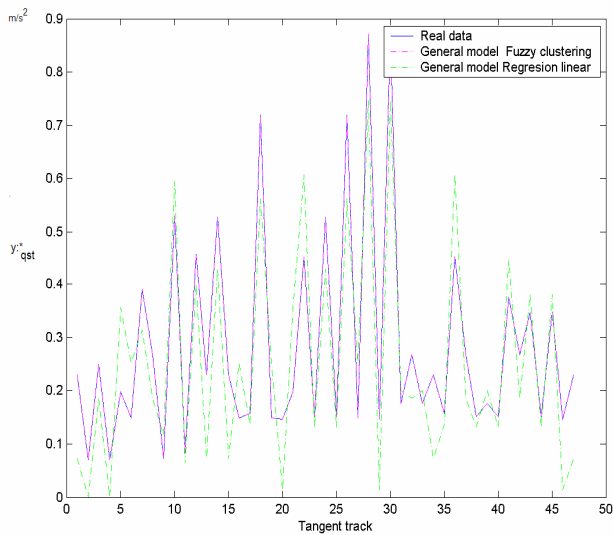
15	41	92.5	92.6
----	----	------	------

Figure 9 shows the measured data of the acceleration and the model output data obtained by fuzzy clustering for the vehicle 05. It is noticeable that in the table of results there is a VAF of 100%, that corresponds with the line at 45° of the figure and besides produced faithfully the acceleration as it is shown in figure 10.

**Figure 9. Plot Yqst vs. Output fuzzy model Vehicle 05.**



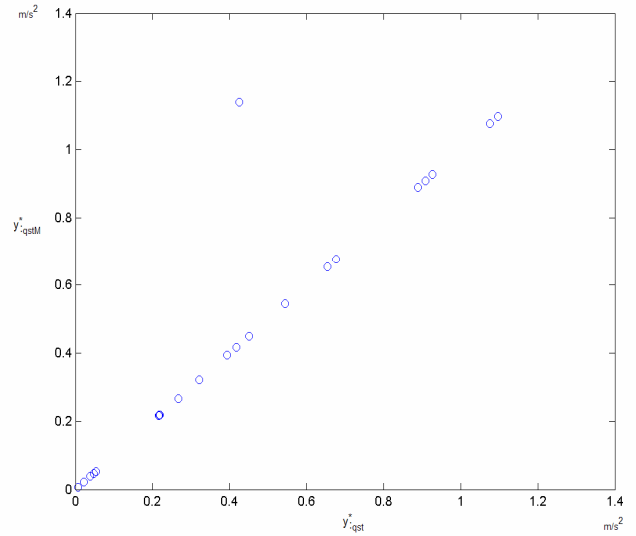
**Figure 10. Real acceleration curve vs. Model curve Vehicle 05.**



In table 3 it is observed that the worst VAF coefficient corresponds to the vehicle 40, with a VAF of 92.28. If we plot the data (see figure 12) it can be clearly observed which model did not estimated well a data, leaving this out of the

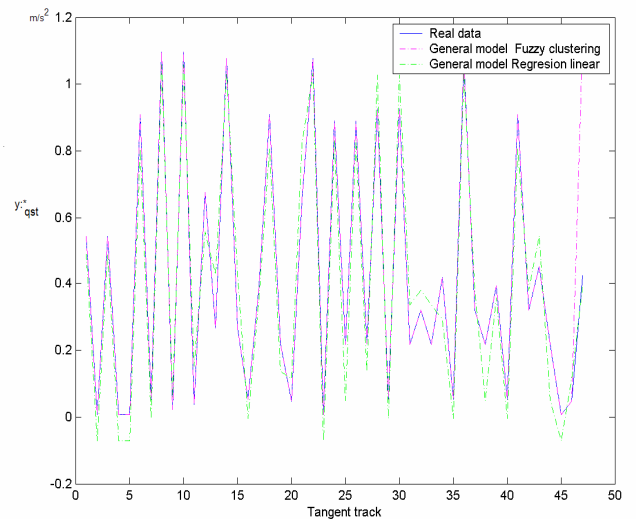
comparative graphic of 45° (Figure 11). This could be because of tuning problems of the model, either in the sensors installation, different geometric conditions of the rail or the equipment capacity, etc.

**Figure 11. Plot Yqst vs. Fuzzy model output. Vehicle 40**

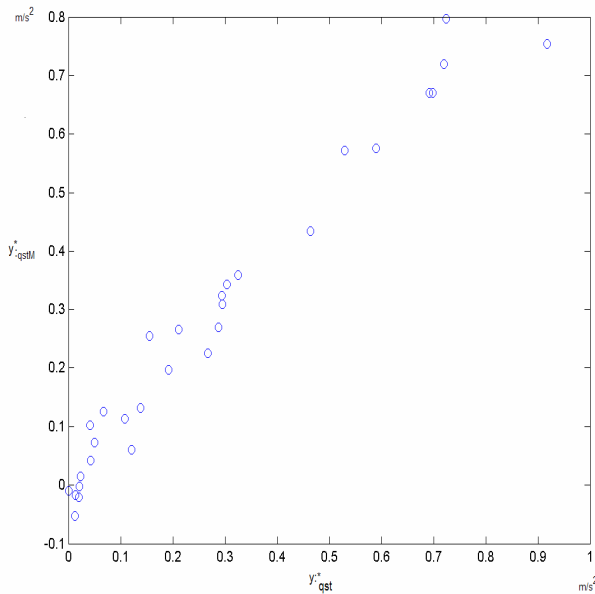


To obtain a general model, all the samples of the 15 vehicles in a matrix were taken, and then a pre-processing consisting of interchanging the files randomly was made. After that, the same process made to the vehicles individually was made and the results were a VAF of 97.35. It can be graphically observed in figures 13 and 14.

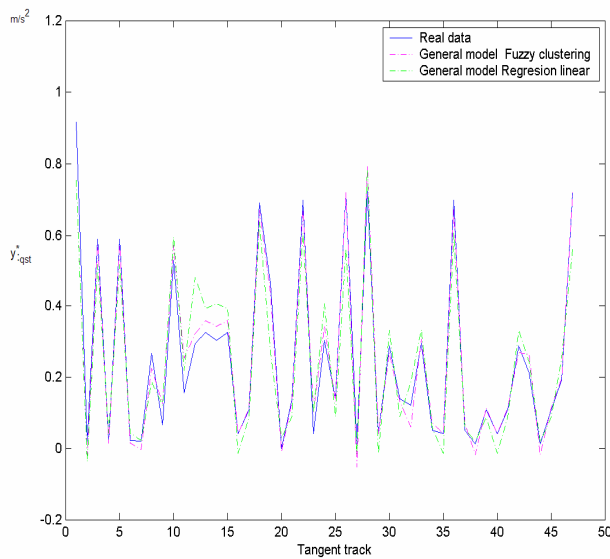
**Figure 12. Real acceleration curve vs. Model curve. Vehicle 40.**



**Figure 13. Plot Yqst vs. Fuzzy general model output.**



**Figure 14. Real acceleration curve vs. General model Curve**



## 6. CONCLUSIONS

In this article, the main Fuzzy clustering aspects for the model identification were revised.

Although the obtained results with the linear multiple regression are satisfactory, comparing the obtained results, we find that the quality of the fuzzy model is better in 14 out of 15 analysed vehicles, and only one vehicle of the model of linear multiple regression is better than with the fuzzy model.

We showed that Fuzzy clustering is a good tool to approximate nonlinear functions, specially the Takagi-Sugeno model.

This regression model can be integrated into the process for decision support in maintenance rail-vehicle interface. To reduce the cost associated in the maintenance work, human resources and increase the reliability of system.

Due to the reasons explained before, when it comes to identify a nonlinear model, we recommend the fuzzy model to be used in future implementations among the SPD.

## 7. ACKNOWLEDGEMENTS

We would finally like to express deep gratitude to EAFIT University, COLCIENCIAS and the Medellín Metro Company for making possible the execution of this document.

## REFERENCES

- [1] DE VEAUX R, SCHUMI J, SCHWEINSBERG J, UNGAR L Prediction intervals for Neural Networks via nonlinear regression Technometrics, vol.40, Issue 4, 1998 pag 273-282 ISSN:0040-1706 USA
- [2] HORNIK K, STINCHCOMBE M, WHITE H Multilayer feedforward networks are universal approximators Neural Networks Vol. 2, Issue 5,1985 pag 359-366 ISSN:1045-9227
- [3] MHASKAR H.N. Neural networks for optimal approximation of smooth and analytic functions Neural computation, vol 8, 1996 pag 164-177 ISSN:0899-7667
- [4] CHEN S, BILLINGS S.A. Representation of non-linear system: the NARMAX model International journal control 49 pag 1012-1032
- [5] SPECHT D.F A general regression neural network IEEE transactions on Neural networks, Vol.2 Issue 6 1991 ISSN: 1045-9227
- [6] NELLES O, Nonlinear system identification: from classical approaches to neural networks and

fuzzy models. Published Springer- Berlin- 2001 ISBN 3-540-67369-5

[7] INTERNATIONAL UNION OF RAILWAYS. UIC CODE 518. Testing and approval of railway vehicles from the point of view of their dynamic behaviour – safety – track fatigue – ride quality. 2nd edition, April 2003. 72 p.

[8] BABUSKA R., Fuzzy modeling for control. Kluwer Academic publishers. 1998 ISBN: 978-0-7923-8154-9

[9] KUMAR M, STOLL R, STOLL N., A min-max approach to fuzzy clustering, estimation, and identification. IEEE transactions on fuzzy system, Vol 14, No 2, 2006 pp 248-262 ISSN: 1063-6706

[10] HWANG C, CHUNG-HOON RHEE F, Uncertain fuzzy clustering: Intervak type-2 fuzzy approach to C-means. IEEE transactions on fuzzy system, Vol 15, No 1, 2007 pp 107 120. ISSN: 1063-6706

[11] HONDA K, ICHIHASHI H, Regularized linear fuzzy clustering and probabilistic PCA mixture models, IEEE transactions on fuzzy system, Vol 13, No 4, 2005 pp 508-516 ISSN:1063-6706

[12] TAKAGI, T. SUGENO, M. Fuzzy Identification of systems and its applications to modeling and control. IEEE Transactions on systems, man, and Cybernetics. Vol. SMC-15. 1985. pp.116-132.

[13] BABUSKA R, Fuzzy modeling and identification toolbox

[14] WALPOLE, Ronald E. y MYERS, Raymond H. Probabilidad y estadística. Ed. 4. México : Mc Graw Hill, 1992, 797p. ISBN 968-422-992-5.

[15] KREYSZIG, Edwin. Introducción a la estadística matemática: principios y métodos. México : Editorial Limusa S.A. 1978, 505p.

[16] ZOLTOWSKI B, CASTAÑEDA L, BETANCOURT G, Monitoreo Multidimensional de la Interfase Vía-Vehículo de un Sistema Ferroviario Congreso Internacional de Mantenimiento – ACIEM – Marzo 2007. Bogotá Colombia

[17] M. ISHIDA, M. AKAMA, K. KASHIWAYA, A. KAPOOR « The current status of theory and practice on rail integrity in Japanese railways—rolling contact fatigue and corrugations ». Fatigue & Fracture of Engineering Materials and Structures, Vol. 26. No 10. 2003. pp.909-919.

[18] ZOETEMAN, A. ESVELD, C. « State of the art in railway maintenance management: planning systems and their application in Europe ».

Systems, Man and Cybernetics, 2004 IEEE International Conference on. Vol. 5. 2004. pp.4165-4170.

[19] OTTOMANELLI M, DELL'ORCO M, SASSANELLI D. « A Decision Support System Based on Neuro-Fuzzy System for Railroad Maintenance Planning ».

<http://dblp.uni-trier.de>

[20] DEBIOLLES A, OUKHELLOU, L. AKNIN, P. « Combined use of partial least squares regression and neural network for diagnosis tasks ». Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on. Vol. 4. 2004. pp.573-576.

[21] DEBIOLLES A, OUKHELLOU, L. AKNIN, P. « Linear and nonlinear regressions using PLS feature selection and NN on defect diagnosis application». Int. Conf. On Machine Intelligence ICMI 2005.

[22] CASTAÑEDA L, ZOLTOWSKI B « Diagnostic System for the metro train ». International Conference on Maintenance Engineering (ICME), Cheng Du, China. October 15-18, 2006.

[23] CASTAÑEDA L, ŻÓŁTOWSKI B Metoda środowiskowych badań pojazdu szybowego. Inżyniera i Aparatura Chemiczna. SIMPress, Gliwice, Poland. 3 specjalne maj 2006 Pag. 100-104. ISSN 0368 - 0827

[24] CASTAÑEDA L, ŻÓŁTOWSKI B Portable Diagnostic System for the Metro Train Diagnostyka, vol. 37, Nr 1 (37) 2006, Olsztyn – Poland. Pag. 39-45. ISSN 641-6414